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Simulation of CO_2-oil minimum miscibility pressure (MMP) for CO_2 enhanced oil recovery (EOR) using neural networks

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Abstract:

CO_2-oil minimum miscibility pressure (MMP) is a key parameter in CO_2 enhanced oil recovery (CO_2-EOR) process. This work developed a fast and vigorous mathematical method using artificial neural network (ANN) model based on genetic algorithm to predict the CO_2-oil MMP which was affected by several factors (i.e. reservoir temperature, the composition of reservoir oil, and the composition of injected gas). The study evaluated the performance of the newly developed ANN-based model by the errors between the predicted values and the target values. It was found that the developed ANN model provided a reliable theoretical basis for CO_2 flooding, as well as offered a guidance to the successful implementation of CO_2-EOR process.

Keywords: CO_2; Minimum miscibility pressure; Artificial neural network; Genetic algorithm; Enhanced oil recovery; Miscible flooding

1. Introduction

Over the last decades, enhanced oil recovery (EOR) has gained considerable attention worldwide since it can improve the amount of crude oil extracted from the mined oil fields. Among the enhanced oil recovery techniques, carbon dioxide (CO_2) flooding is one of the most effective methods because of its high oil recovery rate and the recyclability of the injected CO_2 [1-3]. Consider of the serious environmental effects caused by CO_2 as a major greenhouse gas, it is a good choice to use CO_2 as a flooding agent for EOR process and stores it in the depleted oil reservoir. This concept brings two important benefits: (i) reducing the CO_2 emission, which directly alleviate the serious global warming and climate change problems, and (ii) enhancing oil recovery and, thus, mitigating the world energy shortage problem to some extent.

CO_2-oil minimum miscibility pressure (MMP) is a key parameter in the CO_2 enhanced oil recovery (CO_2-EOR) process since it plays an important role in the design of CO_2 miscible flooding. MMP is the lowest pressure at which the injected gas can achieve dynamic miscibility with the reservoir oil at

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reservoir temperature. The reservoir miscibility is strongly dependent on reservoir pressure that if the pressure is below MMP, the miscible displacement cannot be achieved completely, which may leads to a decrease in the oil recovery rate [4]. On the other hand, CO_2 can miscible with oil easier at a higher pressure. However, excessive reservoir pressure may lead to an increase in initial operation cost as well as professional safety loophole. Given these, a reliable estimation of MMP for a miscible CO_2 flood process is therefore of considerable interest to the petroleum industry, and will bring significant economic and social benefits [5].

Among the recent available methods for MMP determination, the widely used experimental methods include: slim tube test [6-8], rising bubble apparatus (RBA) test [8,9] and vanishing interfacial Tension (VIT) technique [10-12]. Despite their high measurement accuracy, these experimental methods are very costly and time-consuming, which hinder their widespread application. Meanwhile, mathematical correlations relating the MMP to the oil physical properties and injection gas compositions, such as empirical equations and equation of states, have been reported in many literatures [5,6,13- 19]. However, such statistical techniques also have disadvantages since they generally aim to the specific oil reservoir and cannot satisfied with the comprehensive requirements of various oil reservoirs [6,13,14]. Therefore, searching or developing a more adaptable and reliable technique is essential for the determination of MMP. In the recent years, the simulation of CO_2-oil MMP using artificial intelligence have been reported in several studies, such as Mousavi et al. [4], Huang et al. [20], Emera and Sarma [21], Mousavi et al. [22] and Nezhad et al. [23], and achieved good prediction performances. Given this, artificial neural network (ANN)-based model, one method of artificial intelligence, can be an attractive alternative to predict MMP owing to its powerful and effective ability to reflect the system's complexity. ANN can learn from input data, and reflect the system's complexity more effective than conventional statistical techniques [20]. In petroleum industry, ANN has been applied in a number of areas such as well-test analysis, well-log interpretation, field development, reservoir characterization, PVT properties and permeability studies, formation damage, production, and drilling[20,24,25].

In the present work, a universally applicable ANN model was developed to determine the pure and impure CO_2-oil MMP for miscible displacement, and to investigate the effects of MMP-related factors (e.g., reservoir temperature and the composition of injected gas). Firstly, building and optimizing an ANN model according to the fundamental theory of neural network, which contains two aspects: (i) regulating the network structure parameters, and (ii) optimizing the connective weights and biases based on genetic algorithm. Secondly, testing the accuracy and adaptability of the developed model. In addition, the effectiveness of the developed ANN model was evaluated by comparing the prediction results with experimental results, as well as with some other correlations. Finally, the influence degree of each parameter on MMP was also considered.

2. Overview of artificial neural network

ANN is based on the theory of artificial intelligence with the unique abilities for (i) processing information from input variables parallelly, (ii) recognizing the underlying nonlinear relationships within the available inputs and target data, and (iii) touching the detailed mechanism of interactions among various impact factors. In view of these, ANN can be characterized as a computational information processing system with particular abilities for pattern classification, function approximation and linear or nonlinear multivariable systems identification [24].

The basic topology structure of a neural network mainly includes neuron units (neurons), connection strengths (weights), biases (thresholds) and transfer functions [26]. Without loss of generality, an ANN is multi-layered (one input layer, one output layer, and at least one hidden layer). In addition, the network neurons are also classified into three types, which are corresponding to each layer type. The numbers of input and output neurons depend on the complexity of the given system, which corresponding to that of the influence variables and target parameters respectively. By means of the interaction of the weights, biases, and transfer functions, information transfers from the input layer across the hidden layers to the output layer. Then, the network iteratively adjusts its connective weights and biases according to the predicted errors, which are calculated between ANN outputs and target values. When the network was well trained, the non-training data (testing data) are used to assess the accuracy and adaptability of the established network. After trained and tested, the ANN model can then be used to predict the target parameters.

3. Data collection

Data collection is of great importance for obtaining a good dataset that can reflect effectively the underlying nonlinearities, complexities and intricacies of the targeted system behavior. According to the purity of injected CO_2 gas, MMP can be divided into two kinds: pure MMP and impure MMP. The pure MMP is most strongly related to the reservoir temperature (T_R) and the reservoir fluid composition (i.e. mole percentage of volatile oil components (C_1 and N_2), mole percentage of intermediates oil components (C_2-C_4, H_2S and CO_2), and the molecular weight of heavy fractions (C_{5+})). Thus, these parameters are considered as the input variables of the neural network for pure MMP prediction. In the case of impure MMP, it is influenced not only by the four parameters mentioned above, but also by the impurities (C_1, N_2, H_2S, and C_2-C_4) in CO_2 injection gas. Therefore, the impurities are also should be regarded as the input variables. These data were chosen as the inputs of neural network, and applied to develop and validate the new model.

Data used in this study were collected from the literatures [15,16,18,19,27- 42] without any modification or manipulation. After dropping the repeated data sets, there were 83 data sets in total, which included 43 pure CO_2 data and 40 impure CO_2 data. Among them, about 70% of these data were used to train the ANN model, while the remaining 30% were used to test the accuracy and stability of the trained model.

4. The design of ANN model

After collected the proper data, the ANN model was designed as following. At first, a three-layer back-propagation neural network was built up based on the fundamental theory of neural networks. The neural network used for pure MMP prediction is displayed in Fig 1, it showed the basic structure of a network with 4 and 1 neurons in input and output layer respectively. In order to get the optimum model structure, several key parameters (i.e., data pre-processing method, hidden-layer neurons, training algorithm, and transfer functions) should be taken into account. Proper input data presentation is one of the most important steps for network training process to acquire good results as well as to quicken up the calculation and training speed. In this section, a normalization method that scaled data into 0 to 1 was selected as data pre-processing method. By changing the number of neurons in hidden layer, the type of learning algorithm, and the transfer functions of input-hidden and hidden-output layers respectively, the different results for MMP prediction were obtained (which are not listed in this work). By comparing these results, the optimum network with the best structure was achieved, as displays in Table 1.

Once the model structure was confirmed, a genetic algorithm was used to modify the connective weights and biases in order to obtain more accurate predicted result. Initial weights and biases were generated randomly, and scaled into 0 to 1. They were fitting parameters that were assigned to every two neurons in adjacent layers to obtain a mapping from an input vector to the output one. They were defined as the original population of genetic algorithm with a population size of 40 chromosomes. After selection, crossover and mutation of each population, the best chromosomes were selected based on their fitness values. These chromosomes were regarded as the initial weights and biases of the established neural network. Then, the ANN's training process continued iteratively until the desired level of error was reached and the final network was obtained.

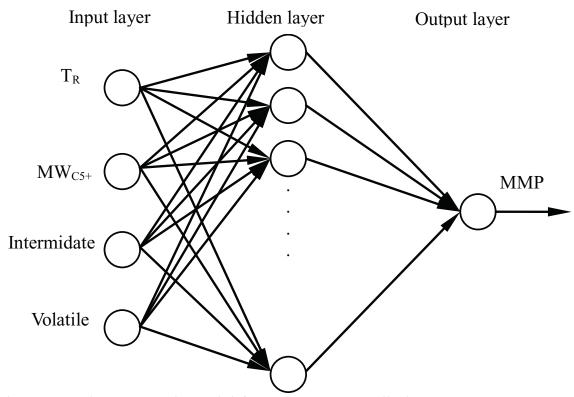

Fig. 1. The structure of Back-Propagation Network model for pure MMP prediction

Table1. The optimized network structure for CO_2-oil MMP simulation

Parameters	Value
Number of neuron in hidden layer	7
Transition function of input-hidden layer	Tansig
Transition function of hidden-output layer	Linear
Input Data form	[0,1]
Function performance	MSE, ARE, AARE,*R*
Performance Value	10^{-4}
Training algorithm	LM

5. Results and Discussion

The accuracy of the developed model was tested by calculating the MMPs of the remaining 30% data sets that were not used in training process and comparing the results of this work with that of several literature correlations. The training and testing results of the developed MMP model are shown in Fig 2-3 and Table 2-4. They display how good agreement between the ANN-based results with the experimental results, which were evaluated by average relative error (ARE), average absolute relative error (AARE), standard deviation (MSE), and the correlation coefficient (R) between the predicted values and the target values.

The simulated training results of pure CO_2-oil MMP as well as those obtained from available literature correlations [5,6,16,21,43] are shown in Fig 2. Obviously, the proposed model had a high accuracy in predicting MMP with a stable and accurate performance. The errors (ARE, AARE, and MSE) and R are listed in Table 2. In addition, the range of absolute relative error was also examined, which were depicted as (i) the minimum (E_{min}) absolute relative error, (ii) the maximum (E_{max}) absolute relative error, and (iii) the percentage of total data that with absolute relative error (APRE) under 2%. It can be seen that the developed ANN-based model had a nearly linear correlation with the experimental data, and the APRE was 56.7%, which found to be the highest among the MMP prediction methods.

Table 2. Comparison of the training CO_2-oil MMP results to the results of different literature correlations. R = correlation coefficient, MSE = standard deviation (%), AARE = average absolute percent relative error, ARE = average percent relative error, E_{min}=minimum absolute percent relative error, E_{max}=maximum absolute percent relative error, APRE= the percentage of total data that with absolute relative error under 2%

Prediction methods	R	ARE	AARE	MSE	E_{min}	E_{max}	APRE
ANN-based model	0.996	-0.8	3.9	5.4	0.03	12	56.7
Shokir [5]	0.998	0.25	2.55	3.11	0.66	5.62	37.5
Emera and Sarma [21]	0.994	0.65	4.05	4.25	0.04	8.22	31.25
Glaso [43]	0.969	-0.85	9.33	7.18	0.46	25.63	12.5
Alston et al.[16]	0.973	-5.37	7.54	7.26	0.28	23.54	18.75
Yelling and Metcalfe [6]	0.844	-14.21	15.73	17.56	1.41	43.37	6.25

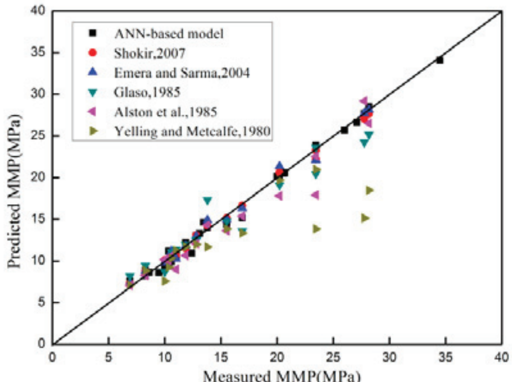

Fig. 2. The parity chart compares the CO_2-oil MMPs obtained from the newly developed ANN-based model with those from literature's correlations

The results of using ANN-based correlation in impure gas-oil MMP prediction in conjunction with the published correlations results [4,5,15,16,21] are shown in Fig 3 and Table 3. It could be clearly observed from Fig 3 that the impure gas-oil MMP results obtained from the present work have more accuracy and acceptability compared with those obtained from other literatures. As evident from Table 3, the newly developed ANN model outperformed the other five reported correlations, especially in terms of stability as indicated by its lowest MSE (4.1%) and highest correlation coefficient (0.992).

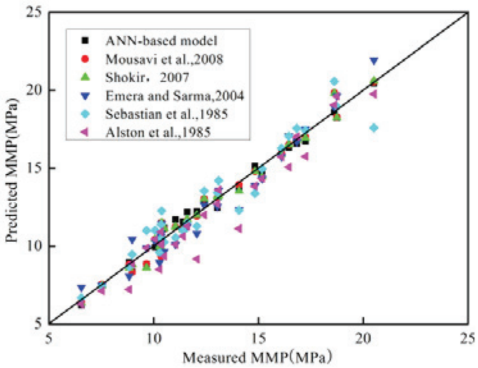

Fig. 3. The parity chart compares the gas-oil MMPs obtained from the newly developed ANN-based model with those from literature's correlations

Table 3. Comparison of the training gas-oil MMP results to the results of different literature correlations (The majuscules in this table represent the same message with Table 2)

Prediction methods	R	ARE	AARE	MSE	E_{min}	E_{max}	APRE
ANN-based model	0.992	-0.18	3.1	4.1	0.12	10.6	46.4
Mousavi et al. [4]	0.991	0.12	3.21	4.16	0.23	10.7	46.4
Shokir,[5]	0.991	0.14	3.3	4.67	0.1	12.17	42.85
Emera and Sarma, [21]	0.976	-0.62	5.72	7.15	0.53	16.28	21.43
Sebastian et al,[15]	0.957	1.37	5.93	7.55	0.95	14.29	28.57
Alston et al.,[16]	0.968	-5.05	6.64	7.51	1.00	24.05	14.29

The testing results of pure and impure CO_2-oil MMP prediction and other two correlations are presented in Table 4. From this table, the newly developed ANN model gives the precise forecast of the pure CO_2-oil MMP with the highest correlation coefficient and the lowest MSE. However, the results of impure CO_2-oil MMP were found to be not as satisfactory as pure MMP because of its ARE, AARE, and MSE were slightly higher than those of Emera and Sarma [21]. This deficiency might be attributable to the over-fitting of network training process and the lack of prediction datasets.

Table 4. Comparison of the testing pure and impure CO_2-oil MMP results to the results of different literature correlations (The majuscules in this table represent the same message with Table 2)

Prediction methods		R	ARE	AARE	MSE
ANN-based model	Pure	0.987	-0.23	3.46	4.46
	impure	0.842	4.4	8.77	10.77
Emera and Sarma [21]	Pure	0.911	5.05	14.39	16
	impure	0.851	-5.3	6.69	9.00
Alston et al. [16]	Pure	0.854	0.01	18.9	23
	impure	0.832	-0.9	9.72	15

6. Sensitivity analysis

Sensitivity analysis was conducted to evaluate the effect of independent parameters (i.e., T_R, composition of reservoir fluid, and composition of injected CO_2 gas) on the dependent variable (CO_2-oil MMP) in conventional oil reservoirs. In this work, the rank correlation coefficient was used to calculate the influence degree of each parameter on MMP. The higher the correlation coefficient between any input variable and output variable means higher significant influence of that input in determining the output's value [5]. Fig 4 shows the results of the sensitivity analysis, which could be described as follows: T_R had a considerable effect on the MMP since the increase of temperature led to a significant increase of the MMP. An increase in the molecular weight of heavy fractions (C_{5+}) or the mole percentage of volatiles oil composition (C_1 and N_2) resulted in an increase of the MMP; while any increase in the intermediate oil composition (C_2-C_4, H_2S, and CO_2) led to a decrease in the MMP, which were correspond well with the works of Mousavi et al. [4] and Shokir [5]. In addition, the effects of impurities in the injected CO_2 gas on the MMP were also investigated. The presence of H_2S or hydrocarbon components (C_2-C_4) had a positive impact on the MMP, for their contribution to lessen the MMP. On the contrary, the existence of C_1 and N_2 in the CO_2 stream brought a higher increase in the MMP and were considered to be negative impact on MMP.

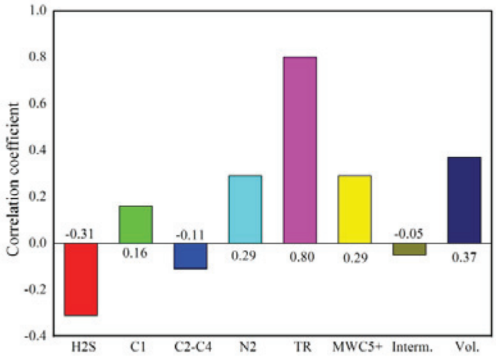

Fig. 4. Sensitivity analysis of the new ANN-based model and the impacts of independent variables on the CO_2-oil MMP

7. Conclusions

In this study, an ANN-based approach that can be used more generally in MMP simulation was developed to predict the pure and impure CO_2-oil MMP in CO_2 miscible displacement process. The following conclusions and recommendations can be drawn based on the discussions on the simulation results:

（1） An ANN-based correlation was selected as an alternative method of the experimental methods and other statistical techniques because of its (i) inexpensiveness and time-saving relative to experimental methods, and (ii) high adaptability and accuracy relative to other statistical techniques.

（2） Reservoir temperature (T_R), composition of reservoir fluid (volatiles, intermediates and C_{5+}) and non-CO_2 components (C_1, N_2, H_2S, and C_2-C_4) in the injected CO_2 gas affect the CO_2-oil MMP. Among these parameters, T_R has the largest effect on the predicted MMP, followed by volatiles and C_{5+}, respectively.

（3） By comparing the results of the newly developed ANN model with experimental results and that of several literature correlations, the ANN-based model has a good performance, which indicates that this model can be used as an effective tool to determine MMP values.

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